PHASE 2 GROUP 7 PROJECT

Business Understanding

Overview

The film industry is a dynamic global market , encompassing all stages of movie creation and distribution, with a powerful cultural and economic influence. As more companies enter the realm of original content, understanding which films resonate most with audiences becomes essential. Analyzing box office trends helps newcomers identify popular genres, profitable themes, and audience preferences, informing smart production choices. This data-driven approach equips new studios to craft engaging content, align with viewer interests, and improve their chances of making a lasting impact in a competitive landscape.

Business Problem

ABC company now sees all the big companies creating original video content and they want to get in on the fun. They have decided to create a new movie studio, but they don't know anything about creating movies. You are charged with exploring what types of films are currently doing the best at the box office. You must then translate those findings into actionable insights that the head of your company's new movie studio can use to help decide what type of films to create

Objectives

1. Identify Popular Film Genres by popularity
2. Identify Emerging Trends and Audience Preferences
3. Identify which type of film are profitable
4. Identify months with highest profit

Data Understanding

After carefully analysising the data provided in relation to the business problem and the business understanding question. we have selected the following datasets :

1. im.db.zip
2. tn.movie_budgets.csv.gz
3. bom.movie_gross.csv.gz

4. tmdb.movies.csv.gz

In [158…
```
# import the packages
import itertools
import numpy as np
import pandas as pd
from numbers import Number
import sqlite3
from scipy import stats
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
import warnings
warnings.filterwarnings('ignore')
from collections import Counter
from collections import defaultdict
from scipy.stats import linregress
import pickle
```

LOADING THE DATA

In [158…
```
bom = pd.read_csv('bom.movie_gross.csv.gz')
tnmovie = pd.read_csv('tn.movie_budgets.csv.gz')
tmdb = pd.read_csv('tmdb.movies.csv.gz')

con = sqlite3.connect("im.db")
imdb = pd.read_sql("""
SELECT *
FROM sqlite_master
"""
, con)
```

Exploring the data

> bom('bom.movie_gross.csv.gz')

In [158…
```
# checking the first two columns
bom.head(2)
```

Out[1585]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010

In [158…
```
# display information about the data
bom.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3387 entries, 0 to 3386
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   title           3387 non-null   object 
 1   studio          3382 non-null   object 
 2   domestic_gross  3359 non-null   float64
 3   foreign_gross   2037 non-null   object 
 4   year            3387 non-null   int64  
dtypes: float64(1), int64(1), object(3)
memory usage: 132.4+ KB
```

> tnmovie('tn.movie_budgets.csv.gz')

In [158…

```
# checking the first two columns
tnmovie.head(2)
```

Out[1587]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875

In [158…

```
# display information about the data
tnmovie.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   id                 5782 non-null   int64 
 1   release_date       5782 non-null   object
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   object
 4   domestic_gross     5782 non-null   object
 5   worldwide_gross    5782 non-null   object
dtypes: int64(1), object(5)
memory usage: 271.2+ KB
```

> tmdb(tmdb.movies.csv.gz)

In [158…

```
# checking the first two rows
tmdb.head(2)
```

Out[1589]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	title
0	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1
1	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon

In [159…

```
# display information about the data
tmdb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26517 entries, 0 to 26516
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Unnamed: 0         26517 non-null  int64  
 1   genre_ids          26517 non-null  object 
 2   id                 26517 non-null  int64  
 3   original_language  26517 non-null  object 
 4   original_title     26517 non-null  object 
 5   popularity         26517 non-null  float64
 6   release_date       26517 non-null  object 
 7   title              26517 non-null  object 
 8   vote_average       26517 non-null  float64
 9   vote_count         26517 non-null  int64  
dtypes: float64(2), int64(3), object(5)
memory usage: 2.0+ MB
```

> imdb

In [159…

```
# checking the first two rows
imdb = pd.read_sql("""
SELECT *
FROM sqlite_master
"""
, con)
imdb.head(2)
```

Out[1591]:

	type	name	tbl_name	rootpage	sql
0	table	movie_basics	movie_basics	2	CREATE TABLE "movie_basics" (\n"movie_id" TEXT...
1	table	directors	directors	3	CREATE TABLE "directors" (\n"movie_id" TEXT,\n...

In [159…

```
# display information about the data
imdb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8 entries, 0 to 7
Data columns (total 5 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   type      8 non-null      object
 1   name      8 non-null      object
 2   tbl_name  8 non-null      object
 3   rootpage  8 non-null      int64 
 4   sql       8 non-null      object
dtypes: int64(1), object(4)
memory usage: 448.0+ bytes
```

Data cleaning

creation of cleaned_gross_budget.csv

we'll create a cleaned_gross_budget.csv by combining the 'bom.movie_gross.csv.gz' and 'tn.movie_budgets.csv.gz'

In [159…

```
# first we rename the column 'title' to 'movie'
bom2 = bom.rename(columns={'title': 'movie'})
# then we drop two columns, 'domestic_gross' and 'year'
bom3 = bom2.drop(['domestic_gross', 'year'], axis=1)
bom3.head(2)
```

Out[1593]:

	movie	studio	foreign_gross
0	Toy Story 3	BV	652000000
1	Alice in Wonderland (2010)	BV	691300000

In [159…

```
# we drop a column, 'id'
tnmovie1 = tnmovie.drop(['id'], axis=1)
tnmovie1.head(2)
```

Out[1594]:

	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875

In [159…

```
# we create a gross_budget dataframe by merging bom3 and tnmovie1
gross_budget= pd.merge(bom3, tnmovie1, on='movie', how='inner')
gross_budget.head(2)
```

Out[1595]:

	movie	studio	foreign_gross	release_date	production_budget	domestic_gross	worldwide_gros
0	Toy Story 3	BV	652000000	Jun 18, 2010	$200,000,000	$415,004,880	$1,068,879,52
1	Inception	WB	535700000	Jul 16, 2010	$160,000,000	$292,576,195	$835,524,64

In [159…

```
# we are removing dollar signs (\$) and commas (,), then converting the values to floa
for col in ['production_budget', 'domestic_gross', 'worldwide_gross']:

    gross_budget[col] = gross_budget[col].replace({'\\$': '', ',': ''}, regex=True).as
gross_budget.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1247 entries, 0 to 1246
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   movie              1247 non-null   object 
 1   studio             1246 non-null   object 
 2   foreign_gross      1086 non-null   object 
 3   release_date       1247 non-null   object 
 4   production_budget  1247 non-null   float64
 5   domestic_gross     1247 non-null   float64
 6   worldwide_gross    1247 non-null   float64
dtypes: float64(3), object(4)
memory usage: 77.9+ KB
```

In [159…

```
# Convert foreign gross, production_budget, domestic_gross, worldwide_gross from strin
gross_budget['foreign_gross'] = pd.to_numeric(gross_budget['foreign_gross'], errors='c
gross_budget['production_budget'] = pd.to_numeric(gross_budget['production_budget'], e
gross_budget['domestic_gross'] = pd.to_numeric(gross_budget['domestic_gross'], errors=
gross_budget['worldwide_gross'] = pd.to_numeric(gross_budget['worldwide_gross'], error
gross_budget.head(2)
```

Out[1597]:

	movie	studio	foreign_gross	release_date	production_budget	domestic_gross	worldwide_gros
0	Toy Story 3	BV	652000000.0	Jun 18, 2010	200000000.0	415004880.0	1.068880e+0
1	Inception	WB	535700000.0	Jul 16, 2010	160000000.0	292576195.0	8.355246e+0

In [159…

```
gross_budget.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1247 entries, 0 to 1246
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   movie              1247 non-null   object 
 1   studio             1246 non-null   object 
 2   foreign_gross      1082 non-null   float64
 3   release_date       1247 non-null   object 
 4   production_budget  1247 non-null   float64
 5   domestic_gross     1247 non-null   float64
 6   worldwide_gross    1247 non-null   float64
dtypes: float64(4), object(3)
memory usage: 77.9+ KB
```

In [159…

```
# checking for missing values
gross_budget.isna().sum()
```

Out[1599]:
```
movie                 0
studio                1
foreign_gross       165
release_date          0
production_budget     0
domestic_gross        0
worldwide_gross       0
dtype: int64
```

In [160…
```
# drop missing values in every colum
for column in gross_budget.columns:
    gross_budget = gross_budget.dropna(subset=[column])

gross_budget.isna().sum()
```

Out[1600]:
```
movie               0
studio              0
foreign_gross       0
release_date        0
production_budget   0
domestic_gross      0
worldwide_gross     0
dtype: int64
```

In [160…
```
# checking how many duplicate rows exist in our DataFrame
gross_budget.duplicated().sum()
```

Out[1601]:
```
0
```

In [160…
```
gross_budget['release_date'] = pd.to_datetime(gross_budget['release_date'])
gross_budget["release_date"] = gross_budget["release_date"].dt.month
```

In [160…
```
gross_budget.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1081 entries, 0 to 1244
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   movie              1081 non-null   object 
 1   studio             1081 non-null   object 
 2   foreign_gross      1081 non-null   float64
 3   release_date       1081 non-null   int64  
 4   production_budget  1081 non-null   float64
 5   domestic_gross     1081 non-null   float64
 6   worldwide_gross    1081 non-null   float64
dtypes: float64(4), int64(1), object(2)
memory usage: 67.6+ KB
```

In [160…
```
# save the cleaned data
gross_budget.to_csv('cleaned_gross_budget.csv', index=False)
```

creation of cleaned_merged_data.csv

we'll create a cleaned_merged_data.csv by combining the 'tmdb.movies.csv.gz' and ''im.db'

In [160…
```
# here we drop columns that we don't need from the tmdb data
tmdb_drop = tmdb.drop(['Unnamed: 0', 'genre_ids', 'title', 'id'], axis=1)
```

```
tmdb_drop.head(2)
```

Out[1605]:

	original_language	original_title	popularity	release_date	vote_average	vote_count
0	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	7.7	10788
1	en	How to Train Your Dragon	28.734	2010-03-26	7.7	7610

In [160…

```
# movie_basic is a table in the imdb database
movbasic = pd.read_sql("""
select *
from movie_basics
;""", con)
movbasic.head(2)
```

Out[1606]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama

In [160…

```
# movie_ratings is also a table in the imdb database
movrating = pd.read_sql("""
select *
from movie_ratings
;""", con)
movrating.head(2)
```

Out[1607]:

	movie_id	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559

In [160…

```
# here we merge the two tables
movies = pd.read_sql("""
select original_title, runtime_minutes, genres, averagerating, numvotes
from movie_basics
join movie_ratings
on movie_basics.movie_id = movie_ratings.movie_id
;""", con)
movies.head(2)
```

Out[1608]:

	original_title	runtime_minutes	genres	averagerating	numvotes
0	Sunghursh	175.0	Action,Crime,Drama	7.0	77
1	Ashad Ka Ek Din	114.0	Biography,Drama	7.2	43

In [160…

```
# now we merge the tmbd and movies data to create a merged_data
merged_data = pd.merge(tmdb_drop, movies, on='original_title', how='inner')
merged_data.head(2)
```

Out[1609]:

	original_language	original_title	popularity	release_date	vote_average	vote_count	runtime_minu
0	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	7.7	10788	14
1	en	How to Train Your Dragon	28.734	2010-03-26	7.7	7610	9

In [161…

```
merged_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 17891 entries, 0 to 17890
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   original_language  17891 non-null  object 
 1   original_title     17891 non-null  object 
 2   popularity         17891 non-null  float64
 3   release_date       17891 non-null  object 
 4   vote_average       17891 non-null  float64
 5   vote_count         17891 non-null  int64  
 6   runtime_minutes    17394 non-null  float64
 7   genres             17831 non-null  object 
 8   averagerating      17891 non-null  float64
 9   numvotes           17891 non-null  int64  
dtypes: float64(4), int64(2), object(4)
memory usage: 1.5+ MB
```

In [161…

```
# checking for null values
merged_data.isna().sum()
```

Out[1611]:

```
original_language      0
original_title         0
popularity             0
release_date           0
vote_average           0
vote_count             0
runtime_minutes      497
genres                60
averagerating          0
numvotes               0
dtype: int64
```

In [161…

```
# drop missing values in every colum
for column in merged_data.columns:
    merged_data = merged_data.dropna(subset=[column])

print(merged_data.isna().sum())
```

```
original_language    0
original_title       0
popularity           0
release_date         0
vote_average         0
vote_count           0
runtime_minutes      0
genres               0
averagerating        0
numvotes             0
dtype: int64
```

In [161…

```
# checking for duplicated rows
merged_data.duplicated().sum()
```

Out[1613]:

```
945
```

In [161…

```
# drop duplicated rows
merged_data = merged_data.drop_duplicates()
merged_data.duplicated().sum()
```

Out[1614]:

```
0
```

In [161…

```
merged_data['release_date'] = pd.to_datetime(merged_data['release_date'])
merged_data["release_date"] = merged_data["release_date"].dt.month
```

In [161…

```
merged_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 16402 entries, 0 to 17890
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   original_language  16402 non-null  object 
 1   original_title     16402 non-null  object 
 2   popularity         16402 non-null  float64
 3   release_date       16402 non-null  int64  
 4   vote_average       16402 non-null  float64
 5   vote_count         16402 non-null  int64  
 6   runtime_minutes    16402 non-null  float64
 7   genres             16402 non-null  object 
 8   averagerating      16402 non-null  float64
 9   numvotes           16402 non-null  int64  
dtypes: float64(4), int64(3), object(3)
memory usage: 1.4+ MB
```

In [161…

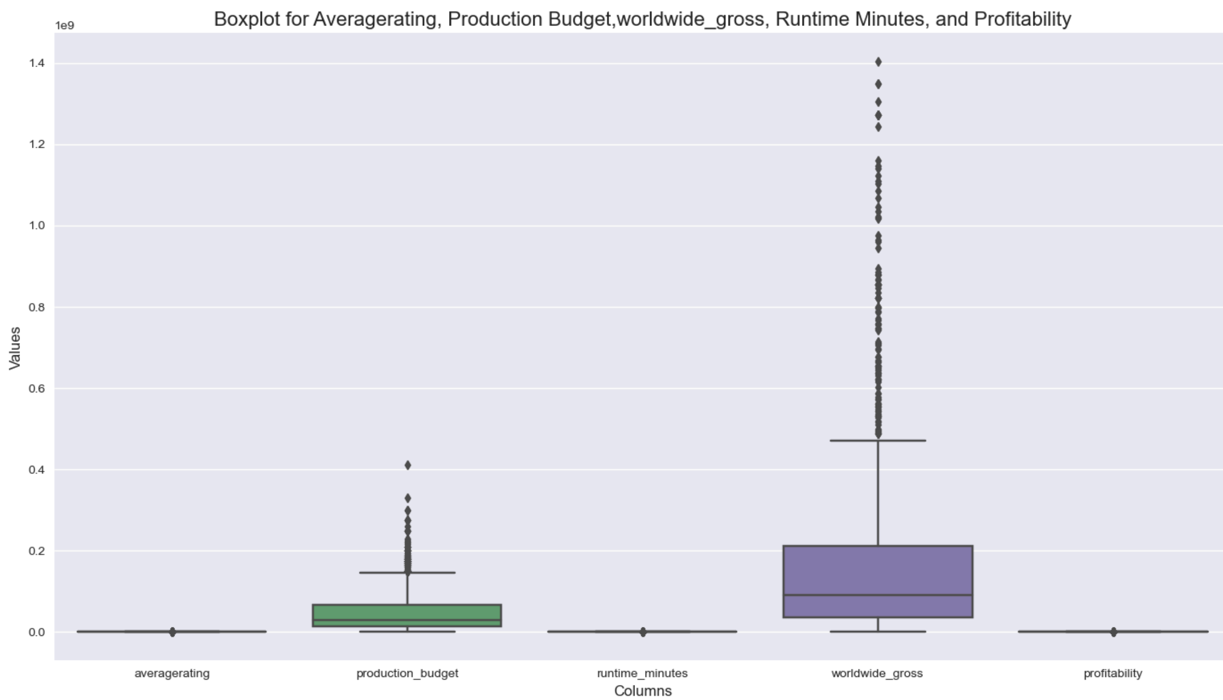
```
# save the cleaned data
merged_data.to_csv('cleaned_merged_data.csv', index=False)
```

merge the two cleaned dataframes for further cleaning

In [161…

```
# Import the data files
gross_budget_df = pd.read_csv('cleaned_gross_budget.csv')
merged_data_df = pd.read_csv('cleaned_merged_data.csv')

#drop the release_date column from the merged_data_df
merged_data_df = merged_data_df.drop(['release_date'], axis=1)
```

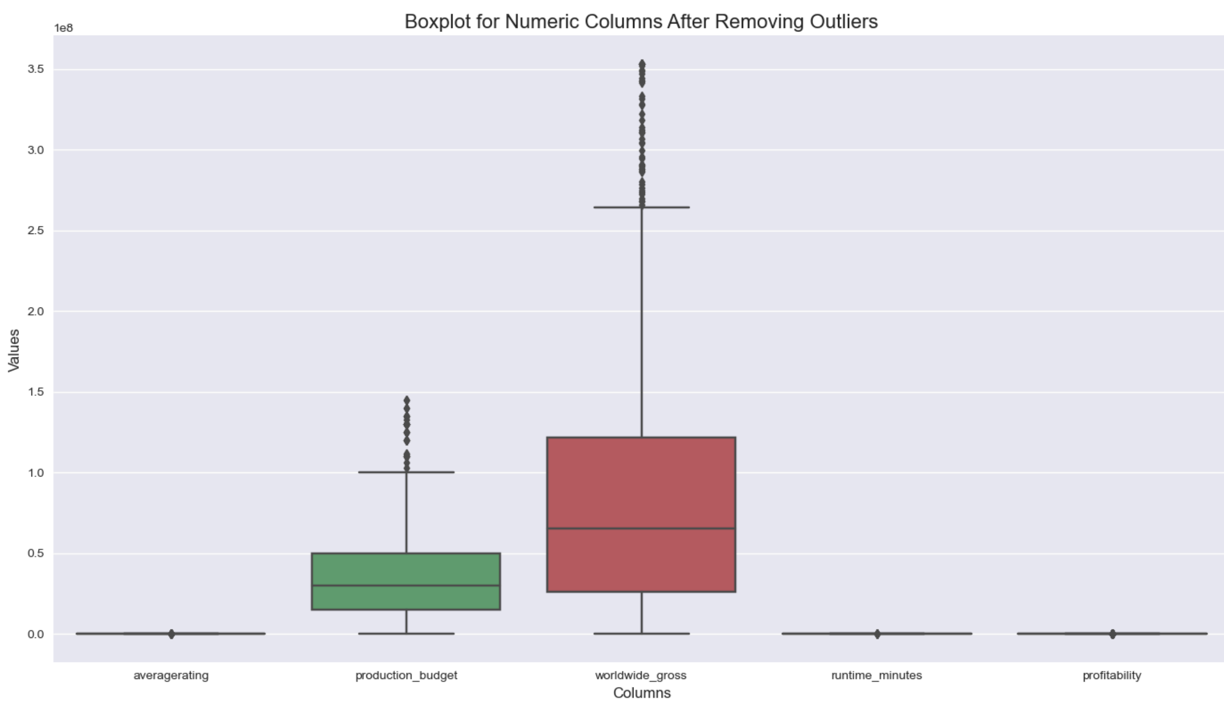
```
# Merge the datasets on 'movie' and 'original_title', with 'cleaned_merged_data.csv' a
df = pd.merge(merged_data_df, gross_budget_df, left_on='original_title', right_on='mov

# add a profitability column
df['profitability'] = (df['worldwide_gross'] - df['production_budget']) / df['producti

# Split the genre column into three parts: genre, genre_class, and genre_class_groupin
df[['genre', 'genre_class', 'genre_class_grouping']] = df['genres'].str.split(',', n=2

# Checkicng for outliers
# Create a new DataFrame with the selected columns for the boxplot
columns_to_plot = ['averagerating', 'production_budget', 'runtime_minutes','worldwide_

# Set up the matplotlib figure
plt.figure(figsize=(14, 8))

# Create the boxplot using Seaborn
sns.boxplot(data=df[columns_to_plot])

# Add title and labels
plt.title('Boxplot for Averagerating, Production Budget,worldwide_gross, Runtime Minut
plt.xlabel('Columns', fontsize=12)
plt.ylabel('Values', fontsize=12)

# Show the plot
plt.tight_layout()
plt.show()
```



In [161…

```
# Use a function to remove outlier from multiple relevant columns using IQR method
def remove_outliers(df, columns):
    for column in columns:
        Q1 = df[column].quantile(0.25)
        Q3 = df[column].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR
        df = df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]
```

```
    return df

# Remove outliers from specified columns
numeric_columns = ['averagerating', 'production_budget', 'worldwide_gross', 'runtime_m
df_cleaned = remove_outliers(df, numeric_columns)

# Define the numeric columns you want to plot
numeric_columns = ['averagerating', 'production_budget', 'worldwide_gross', 'runtime_m

# Set up the matplotlib figure
plt.figure(figsize=(14, 8))

# Create the boxplot using Seaborn
sns.boxplot(data=df_cleaned[numeric_columns])

# Add title and labels
plt.title('Boxplot for Numeric Columns After Removing Outliers', fontsize=16)
plt.xlabel('Columns', fontsize=12)
plt.ylabel('Values', fontsize=12)

# Show the plot
plt.tight_layout()
plt.show()
```



In [162…

```
df_cleaned.dropna()
```

Out[1620]:

	original_language	original_title	popularity	vote_average	vote_count	runtime_minutes	
7	en	Megamind	22.855	6.8	3635	95.0	Ac
12	en	The Expendables	21.517	6.1	4647	103.0	A
14	en	Saw 3D	20.370	6.0	1488	90.0	
16	en	The Book of Eli	18.985	6.7	3495	118.0	A
21	en	The A-Team	17.097	6.3	2703	117.0	A
...	...	...	...	...	...	...	
15143	en	A Wrinkle in Time	12.529	5.0	1073	109.0	A
15162	en	Paul, Apostle of Christ	12.005	7.1	98	108.0	Adve
15170	en	The 15:17 to Paris	11.576	5.3	799	94.0	B
15264	en	Proud Mary	9.371	5.5	259	89.0	
15838	en	Bilal: A New Breed of Hero	2.707	6.8	54	105.0	Actio

548 rows × 20 columns

In [162…

```
df_cleaned.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 899 entries, 7 to 15838
Data columns (total 20 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   original_language      899 non-null    object 
 1   original_title         899 non-null    object 
 2   popularity             899 non-null    float64
 3   vote_average           899 non-null    float64
 4   vote_count             899 non-null    int64  
 5   runtime_minutes        899 non-null    float64
 6   genres                 899 non-null    object 
 7   averagerating          899 non-null    float64
 8   numvotes               899 non-null    int64  
 9   movie                  899 non-null    object 
 10  studio                 899 non-null    object 
 11  foreign_gross          899 non-null    float64
 12  release_date           899 non-null    float64
 13  production_budget      899 non-null    float64
 14  domestic_gross         899 non-null    float64
 15  worldwide_gross        899 non-null    float64
 16  profitability          899 non-null    float64
 17  genre                  899 non-null    object 
 18  genre_class            778 non-null    object 
 19  genre_class_grouping   548 non-null    object 
dtypes: float64(10), int64(2), object(8)
memory usage: 147.5+ KB
```

DATA ANALYSIS

EXPLORATORY DATA ANALYSIS(EDA)

Aggregate analysis

What are the top 10 movie genres by average rating?

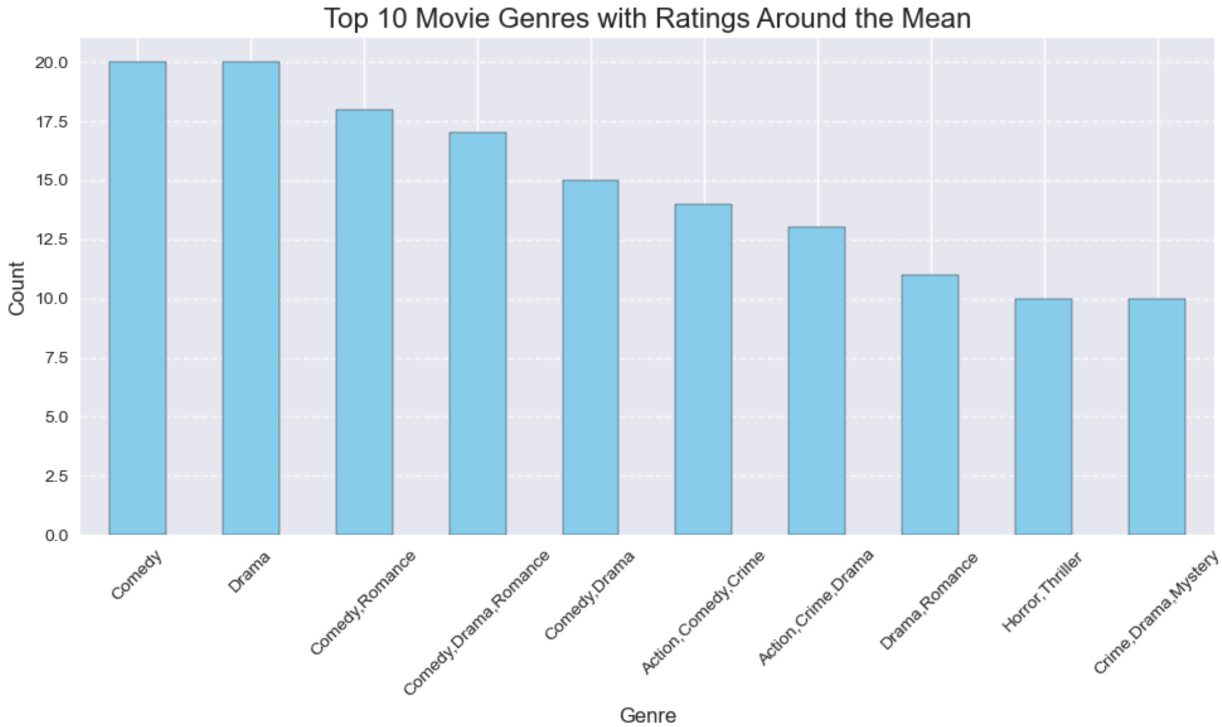
What are the top 10 most profitable movie genres?

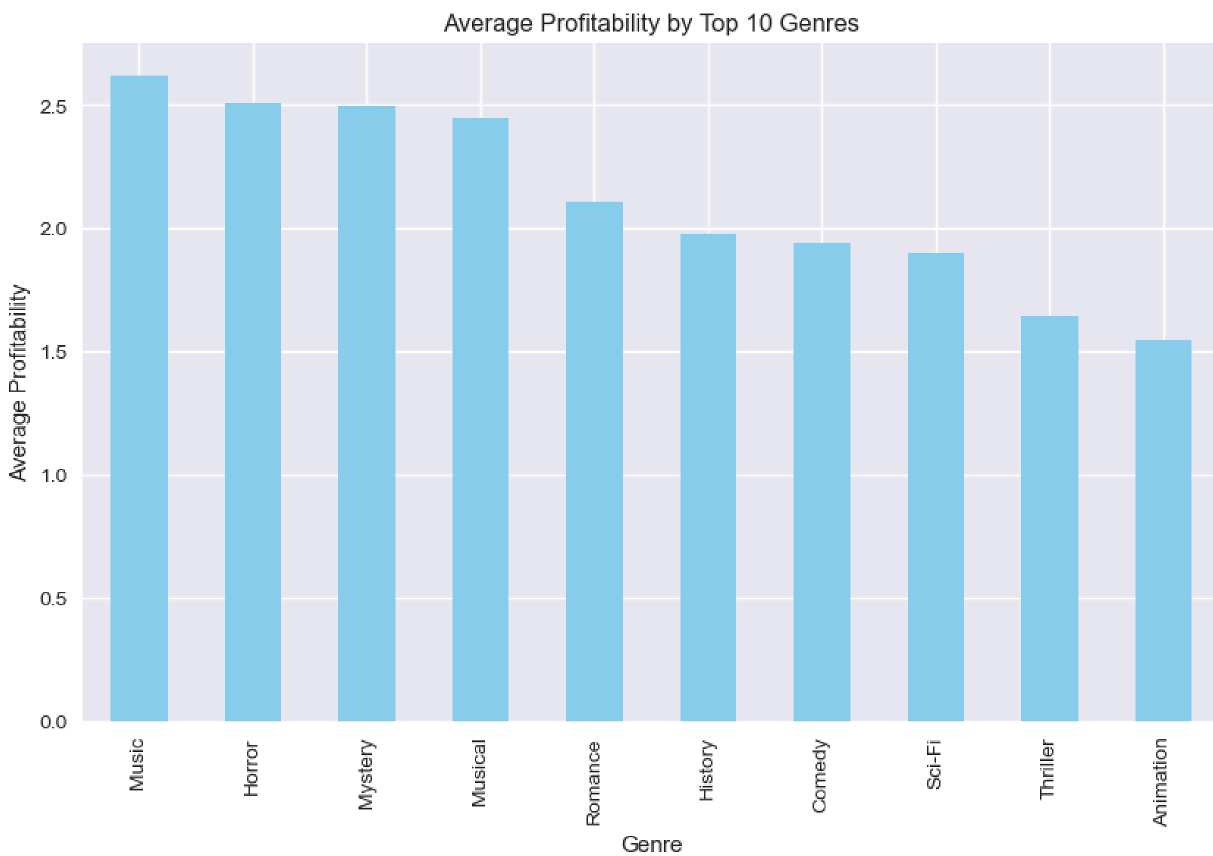
According to the release time, which months generate the highest profits?

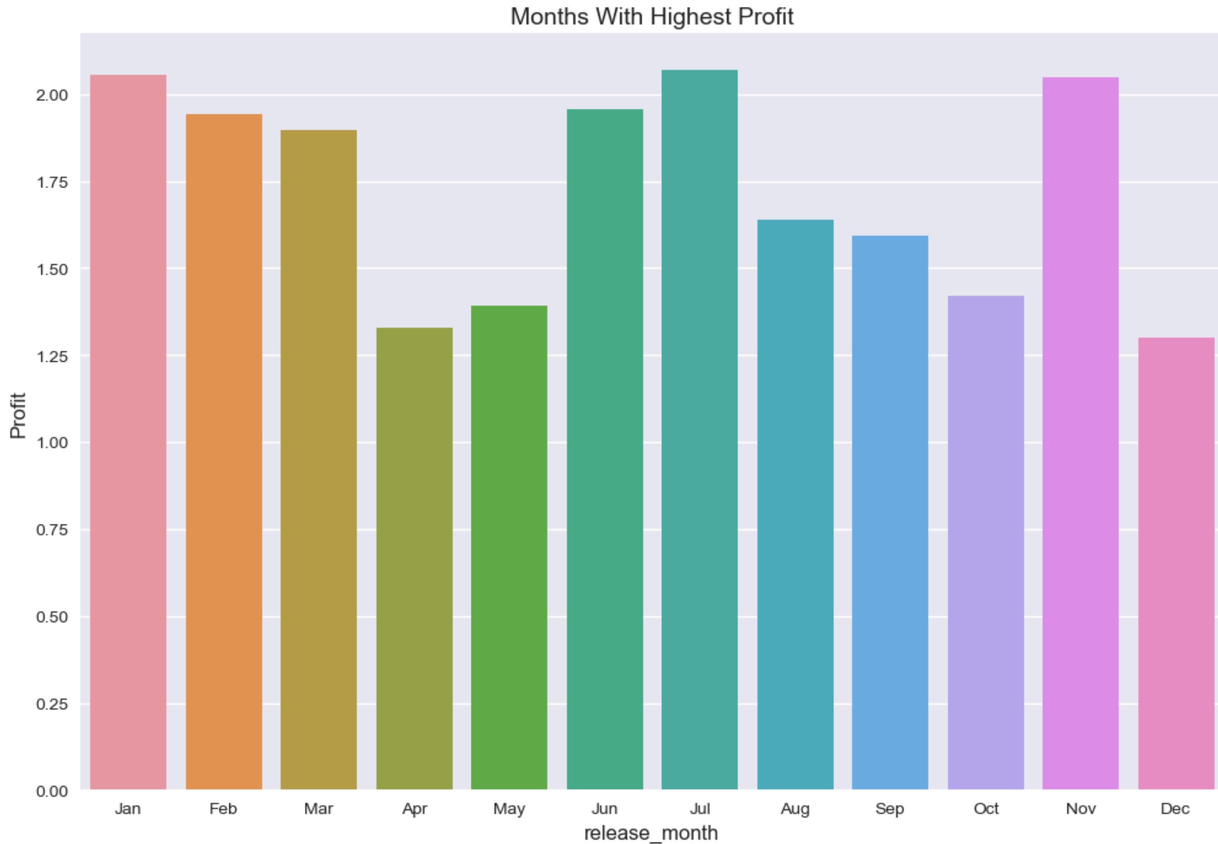
In [162…

```python
# Calculate the mean average rating
mean_rating = df_cleaned['averagerating'].mean()

genre_counts = filtered_df['genres'].value_counts().head(10)

# Plot the bar graph
plt.figure(figsize=(10, 6))
genre_counts.plot(kind='bar', color='skyblue', edgecolor='black')
plt.title('Top 10 Movie Genres with Ratings Around the Mean', fontsize=16)
plt.xlabel('Genre', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.xticks(rotation=45)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()# Split genres in each row and associate profitability with each ger
split_genres = []
profits = []
```

```
for index, row in df_cleaned.iterrows():
    genre_split = row["genres"].split(',')
    split_genres.extend(genre_split)
    profits.extend([row["profitability"]] * len(genre_split))

# Create a new DataFrame with split genres and profitability
split_genre_df = pd.DataFrame({
    'genre': split_genres,
    'profitability': profits,
    'production_budget': df_cleaned['production_budget'].repeat(df_cleaned['genres'].s
})

# Plot for profitability by top 10 genres
top_genres = split_genre_df.groupby('genre')['profitability'].median().nlargest(10).in
avg_profitability = split_genre_df[split_genre_df['genre'].isin(top_genres)].groupby('
avg_profitability = avg_profitability.sort_values(ascending=False)
plt.figure(figsize=(10, 6))
avg_profitability.plot(kind='bar', color='skyblue')
plt.title('Average Profitability by Top 10 Genres')
plt.xlabel('Genre')
plt.ylabel('Average Profitability')
plt.xticks(rotation=90)
plt.show()

# here we write a code that returns a Series with release_date as the index and the av
month_profit = df_cleaned.groupby('release_date')['profitability'].mean()
# covert month_profit into a DataFrame
monthly_profit_df = pd.DataFrame(month_profit)
monthly_profit_df.reset_index(drop=False, inplace=True)
# Assuming 'monthly_profit_df' is a DataFrame with 'release_date' and 'profitability'

fig, ax = plt.subplots(figsize=(12, 8))

# You can directly pass the DataFrame column names to sns.barplot using the 'x' and 'y
sns.barplot(x='release_date', y='profitability', data=monthly_profit_df, ax=ax)

ax.set_title('Months With Highest Profit', fontsize=14)
ax.set_xlabel("release_month", fontsize=12)
ax.set_ylabel("Profit", fontsize=12)
ax.set_xticks(ticks=range(0, 12), labels=['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'J

fig.savefig('Months With Highest Profit.png')
```


Top 10 Movie Genres with Ratings Around the Mean
Count
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
Comedy
Drama
Comedy,Romance
Comedy,Drama,Romance
Comedy,Drama
Action,Comedy,Crime
Action,Crime,Drama
Drama,Romance
Horror,Thriller
Crime,Drama,Mystery
Genre


Average Profitability by Top 10 Genres
Average Profitability
2.5
2.0
1.5
1.0
0.5
0.0
Music
Horror
Mystery
Musical
Romance
History
Comedy
Sci-Fi
Thriller
Animation
Genre



- Most consistently rated genres are Drama and Comedy, the highest profitability is seen in Music and Horror genres, and releasing films in January, July, and November tends to maximize profits.

Descriptive statistics

In [162…

```
# List of columns to analyze
columns_to_analyze = ['averagerating', 'production_budget', 'worldwide_gross', 'runtim

# Check if columns exist in the DataFrame
missing_columns = [col for col in columns_to_analyze if col not in df_cleaned.columns]
if missing_columns:
    print(f"The following columns are missing from the DataFrame: {missing_columns}")
else:
    # Select the relevant columns
    selected_data = df_cleaned[columns_to_analyze]

    # Perform descriptive statistics
    descriptive_stats = selected_data.describe()

    # Display the statistics
    print("Descriptive Statistics:")
    print(descriptive_stats)
```

```
Descriptive Statistics:
       averagerating  production_budget  worldwide_gross  runtime_minutes  \
count     899.000000       8.990000e+02     8.990000e+02       899.000000   
mean        6.313904       3.687570e+07     8.825520e+07       106.056730   
std         0.963057       3.013051e+07     8.189584e+07        15.322666   
min         2.100000       4.000000e+05     0.000000e+00        62.000000   
25%         5.800000       1.500000e+07     2.606169e+07        95.000000   
50%         6.400000       3.000000e+07     6.528273e+07       105.000000   
75%         7.000000       5.000000e+07     1.216812e+08       116.000000   
max         9.200000       1.450000e+08     3.528311e+08       148.000000   

       profitability  
count     899.000000  
mean        1.715422  
std         2.064894  
min        -1.000000  
25%         0.236622  
50%         1.242847  
75%         2.533632  
max         8.525090  
```

- The descriptive statistics reveal that the average movie has a moderate rating (mean rating of 6.36), with budgets and worldwide grosses varying widely (mean budgets around 38.6 million and gross around 90.9 million) and runtime averaging approximately 106 minutes. Profitability exhibits substantial variability, with a mean of 1.68 and a large standard deviation (2.82), indicating that while some movies are highly profitable, others experience losses, as shown by the negative minimum profitability value. The wide ranges and standard deviations across financial metrics suggest high variability in movie performance and budgets.

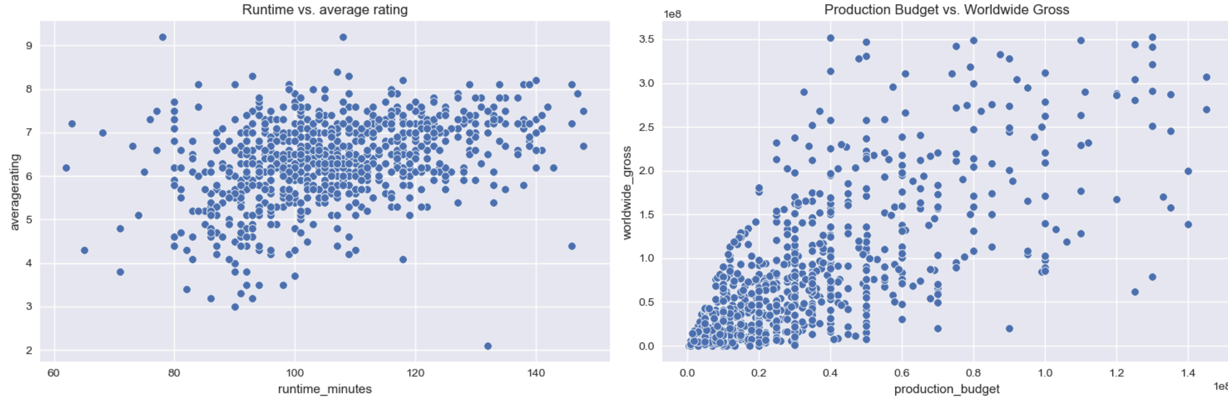
Variable relationships

Is there a relationship between a movie's runtime and its user rating?

How does production budget impact a movie's box office revenue?

In [162…

```
# Scatter plots
fig, axes = plt.subplots(1, 2, figsize=(15, 5))

# runtime vs vote_average
sns.scatterplot(data=df_cleaned, x='runtime_minutes', y='averagerating', ax=axes[0])
axes[0].set_title('Runtime vs. average rating')

# production_budget vs worldwide_gross
sns.scatterplot(data=df_cleaned, x='production_budget', y='worldwide_gross', ax=axes[1
axes[1].set_title('Production Budget vs. Worldwide Gross')

plt.tight_layout()
plt.show()
```

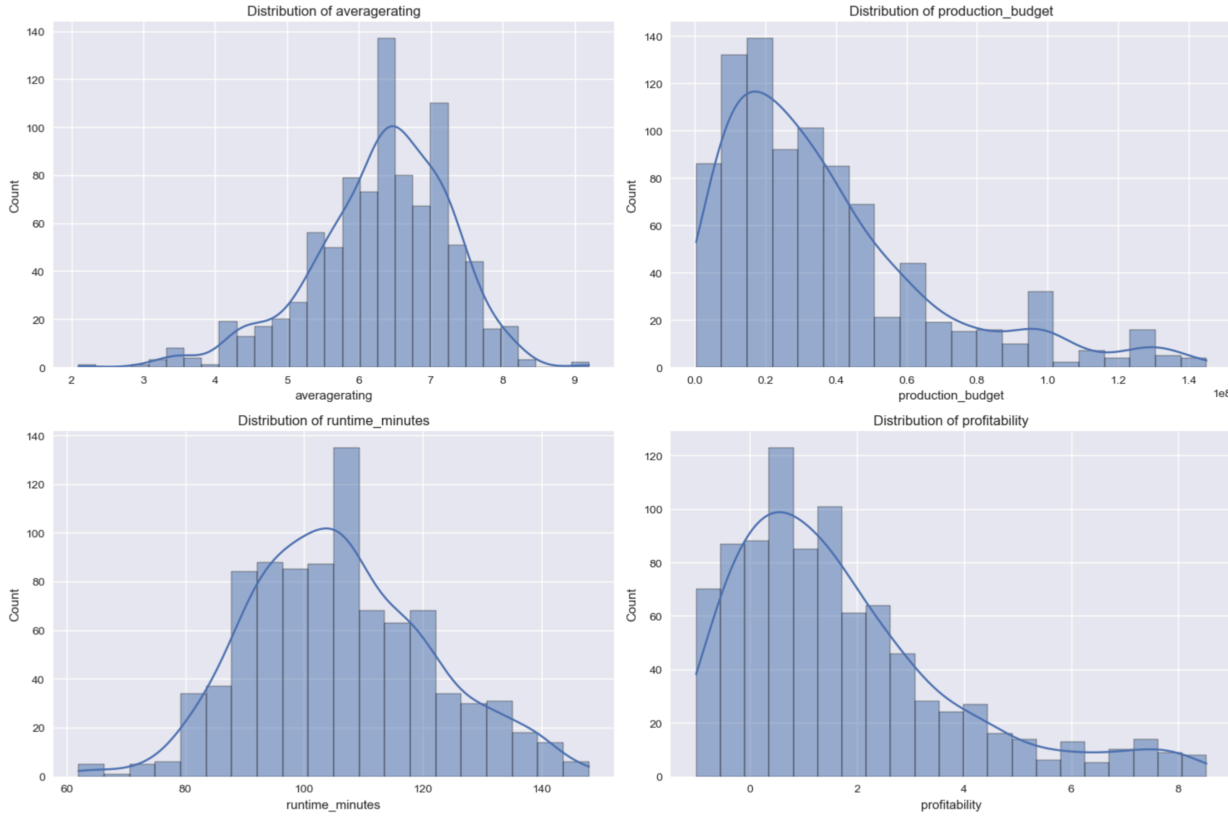


- The scatter plots show a weak positive relationship between runtime_minutes and averagerating, indicating that movie runtime has little effect on user ratings, while production_budget and worldwide_gross exhibit a more noticeable positive trend, suggesting that higher budgets tend to correspond with higher box office revenues.

STATISTICAL DISTRIBUTION

In [162…

```
# Plot distributions
columns_to_plot = ['averagerating', 'production_budget', 'runtime_minutes', 'profitabi
fig, axes = plt.subplots(2, 2, figsize=(15, 10))
axes = axes.flatten()

for i, col in enumerate(columns_to_plot):
    sns.histplot(df_cleaned[col], kde=True, ax=axes[i])
    axes[i].set_title(f'Distribution of {col}')

plt.tight_layout()
plt.show()
```



- The data appears to be visibly normally distributed for average rating, production budget, and profitability, while runtime minutes are skewed right, with most movies falling between 90 and 120 minutes.

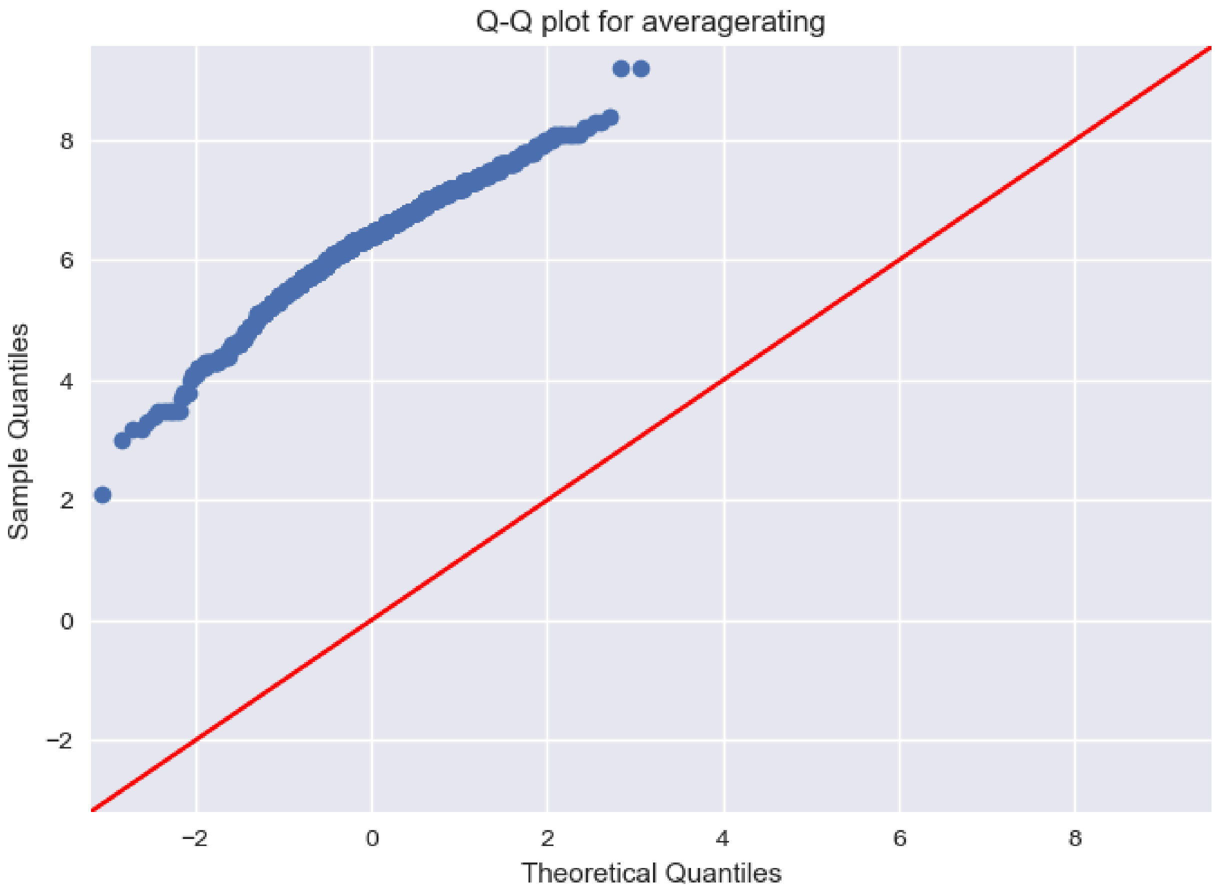
Normality Test

Perform normality test using the Jarque-Bera Test

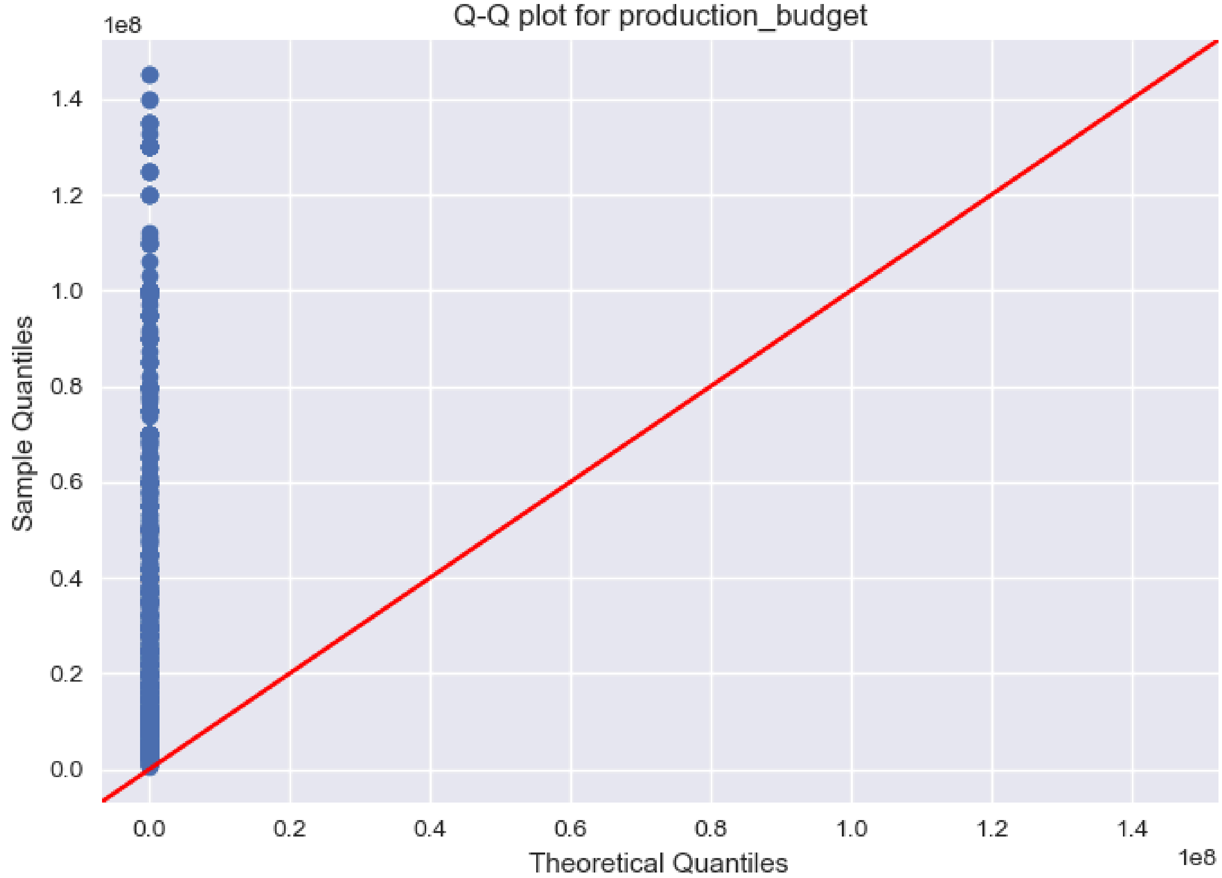
In [162…

```
# List of columns to test for normality
columns_to_test = ['averagerating', 'production_budget', 'runtime_minutes', 'profitabi

# Testing for normality using the Jarque-Bera test
for col in columns_to_test:
    # Drop NaN values for the column
    data = df_cleaned[col].dropna()

    # Jarque-Bera Test
    jarque_bera_stat, jarque_bera_p_value = stats.jarque_bera(data)
    print(f'>> Jarque-Bera test for {col}: Statistic={jarque_bera_stat}, p-value={jarq

    # Interpretation
    if jarque_bera_p_value < 0.05:
        print(f"{col} is likely not normally distributed (reject H0 at alpha=0.05).")
    else:
        print(f"{col} is likely normally distributed (fail to reject H0 at alpha=0.05)

    # Visual Check: Q-Q Plot
    plt.figure(figsize=(6,6))
    sm.qqplot(data, line ='45')  # 45-degree reference line
    plt.title(f'Q-Q plot for {col}')
    plt.show()
```

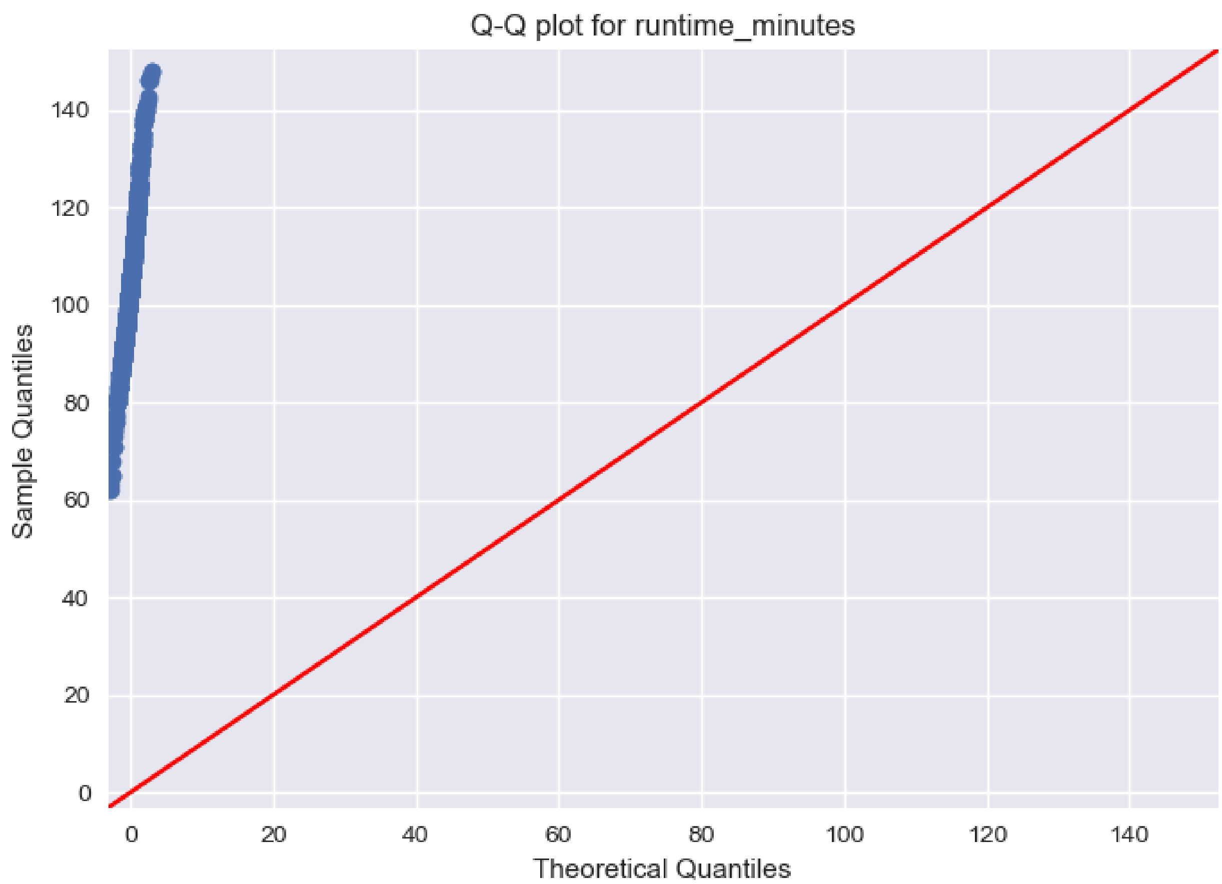
```
>> Jarque-Bera test for averagerating: Statistic=87.54385989464758, p-value=0.0
averagerating is likely not normally distributed (reject H0 at alpha=0.05).
<Figure size 600x600 with 0 Axes>
```



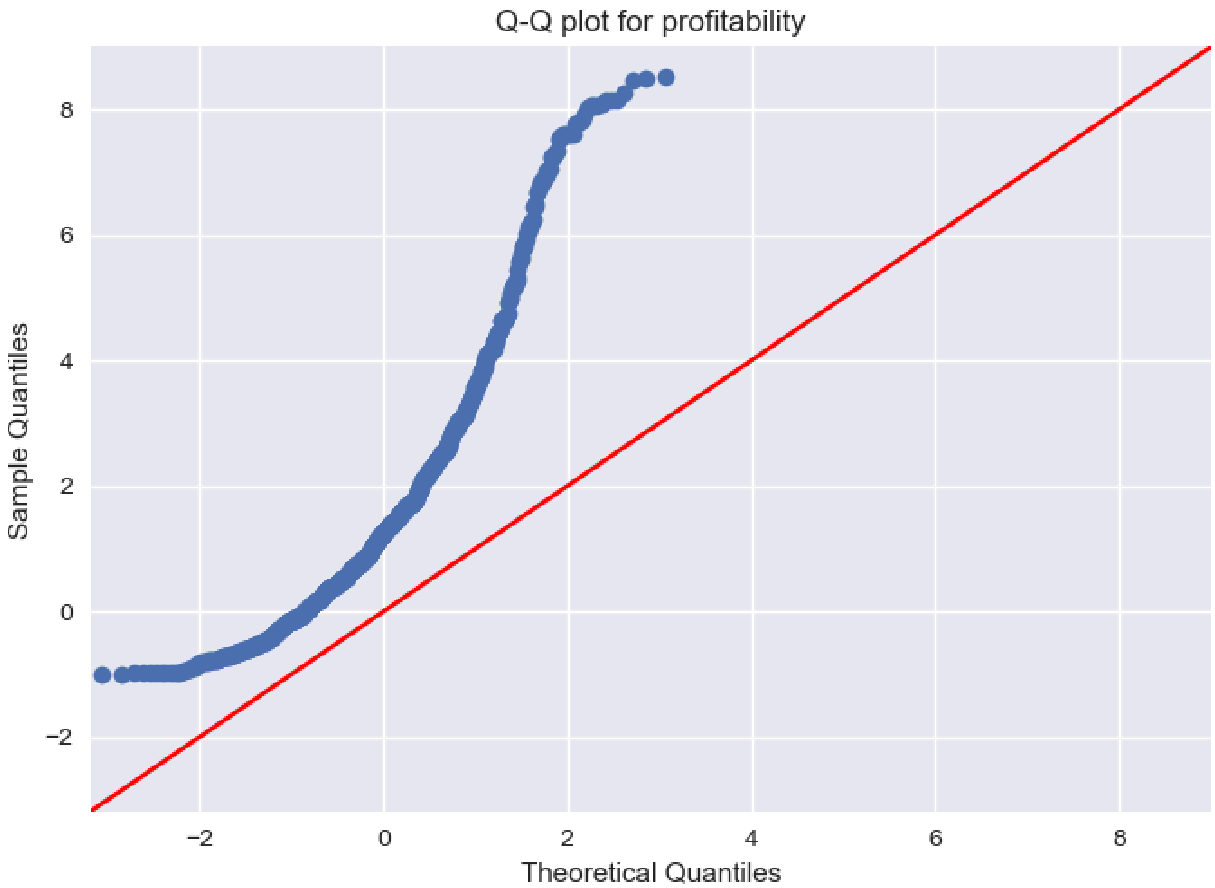

```
>> Jarque-Bera test for production_budget: Statistic=381.3401898550876, p-value=0.0
production_budget is likely not normally distributed (reject H0 at alpha=0.05).
<Figure size 600x600 with 0 Axes>
```




```
>> Jarque-Bera test for runtime_minutes: Statistic=11.527029141336298, p-value=0.0031
400562328601778
runtime_minutes is likely not normally distributed (reject H0 at alpha=0.05).
<Figure size 600x600 with 0 Axes>
```



```
>> Jarque-Bera test for profitability: Statistic=291.5205379951693, p-value=0.0
profitability is likely not normally distributed (reject H0 at alpha=0.05).
<Figure size 600x600 with 0 Axes>
```



-The Jarque-Bera test results indicate that all the variables analyzed—averagerating, production_budget, runtime_minutes, and profitability—are not normally distributed

Normalization

Use Log Transformations to normalize the columns

In [162…

```
# Assuming df_cleaned is your dataframe and columns to be normalized are mentioned
columns_to_transform = ['averagerating', 'production_budget', 'runtime_minutes', 'prof

# Define a function to apply Box-Cox (for positive values) or Yeo-Johnson (for mixed v
def normalize_data(df, columns):
    normalized_data = pd.DataFrame()

    for col in columns:
        # Check if the column contains negative or zero values
        if (df[col] <= 0).any():
            # Use Yeo-Johnson transformation if there are non-positive values
            normalized_data[col], _ = stats.yeojohnson(df[col].dropna())
        else:
            # Use Box-Cox transformation for positive values
            normalized_data[col], _ = stats.boxcox(df[col].dropna())

    return normalized_data
```

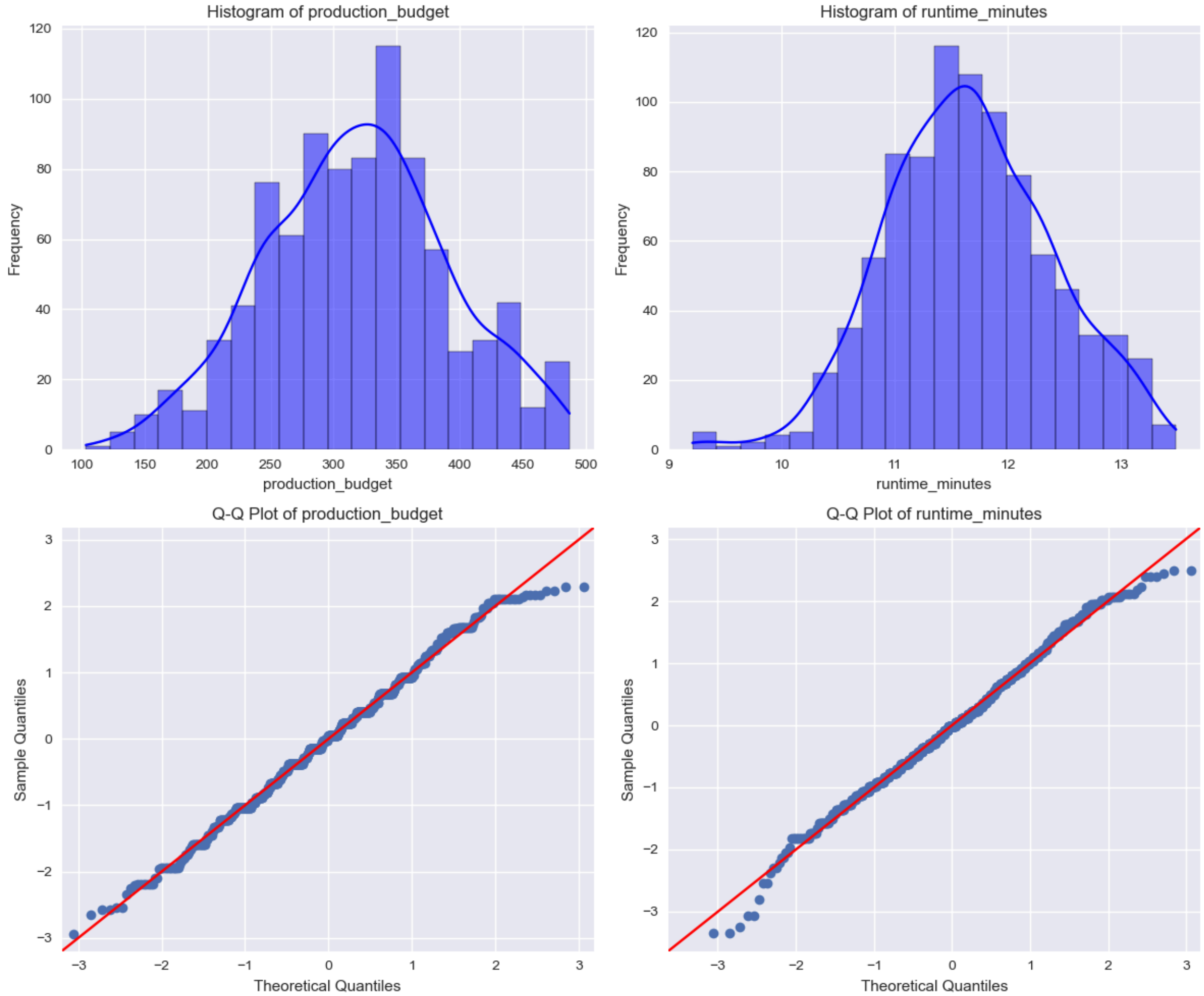
```
# Apply the transformation
normalized_df = normalize_data(df_cleaned, columns_to_transform)

# Print out the first few rows of the transformed data
print(normalized_df.head())
```

```
   averagerating  production_budget  runtime_minutes  profitability
0      36.407069         473.222573        11.149541       1.028770
1      28.052604         419.837516        11.549872       1.399563
2      20.040012         278.674826        10.888052       2.769863
3      32.082816         417.151815        12.248977       0.753627
4      45.951850         417.151815        13.096168       1.589197
```

Display distribution after normalization

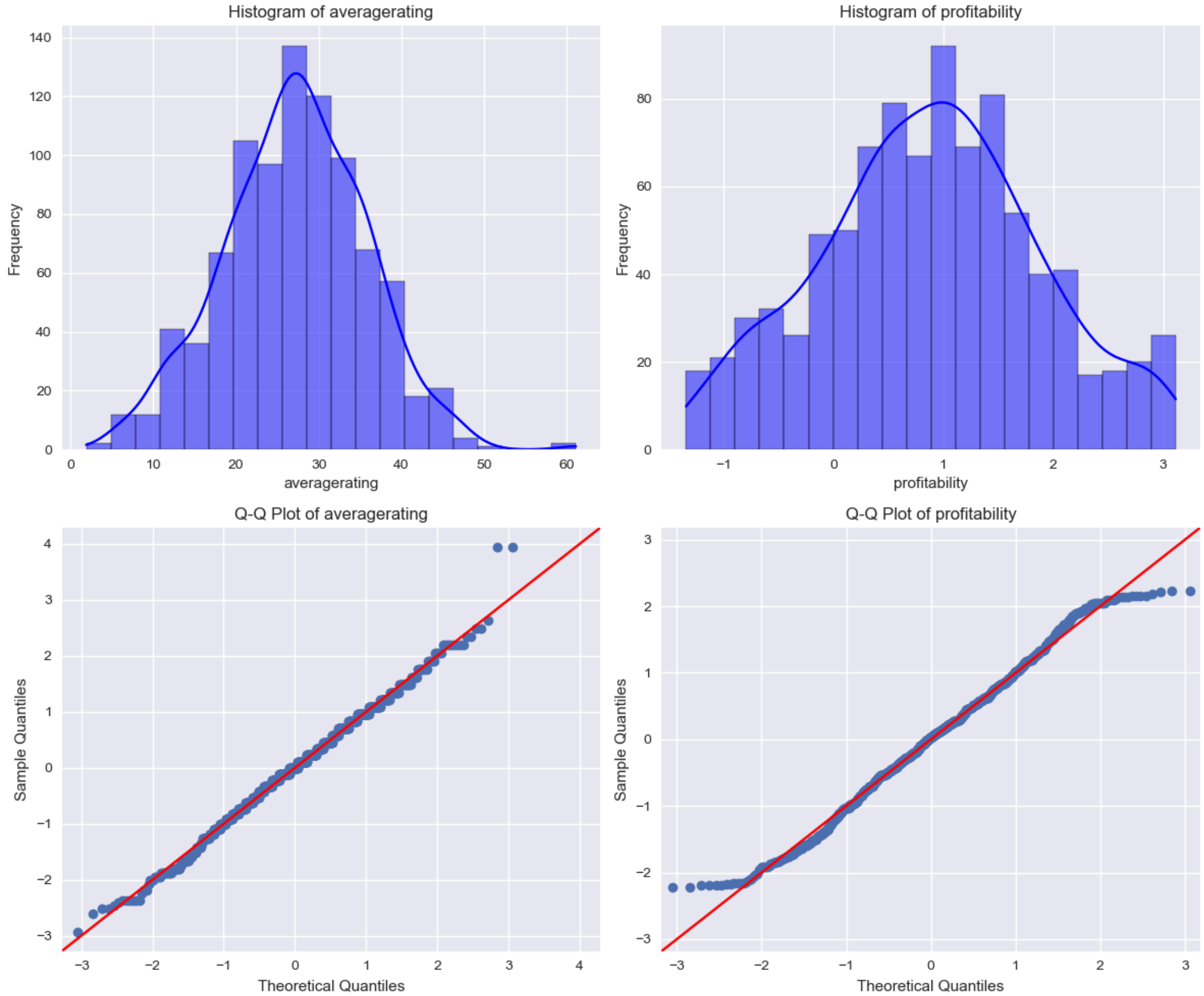
In [162…

```
# Display the distributions in the normally distributed columns
# Select the columns that are likely normally distributed
normal_columns = ['production_budget', 'runtime_minutes']

# Set up plot layout
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(12,10))

# Plot histograms
for i, col in enumerate(normal_columns):
    # Histogram
    sns.histplot(normalized_df[col], bins=20, kde=True, color="blue", ax=axes[0, i])
    axes[0, i].set_title(f"Histogram of {col}")
    axes[0, i].set_xlabel(col)
    axes[0, i].set_ylabel("Frequency")

    # Q-Q Plot
    sm.graphics.qqplot(normalized_df[col], dist=stats.norm, line='45', fit=True, ax=ax
    axes[1, i].set_title(f"Q-Q Plot of {col}")
    axes[1, i].set_xlabel("Theoretical Quantiles")
    axes[1, i].set_ylabel("Sample Quantiles")

# Adjust layout
fig.tight_layout()
plt.show()
```



In [162…

```
# Display the distributions in the normally distributed columns
# Select the columns that are likely normally distributed
normal_columns = ['averagerating', 'profitability']

# Set up plot layout
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(12,10))

# Plot histograms
for i, col in enumerate(normal_columns):
    # Histogram
    sns.histplot(normalized_df[col], bins=20, kde=True, color="blue", ax=axes[0, i])
    axes[0, i].set_title(f"Histogram of {col}")
    axes[0, i].set_xlabel(col)
    axes[0, i].set_ylabel("Frequency")

    # Q-Q Plot
    sm.graphics.qqplot(normalized_df[col], dist=stats.norm, line='45', fit=True, ax=ax
    axes[1, i].set_title(f"Q-Q Plot of {col}")
    axes[1, i].set_xlabel("Theoretical Quantiles")
    axes[1, i].set_ylabel("Sample Quantiles")

# Adjust layout
fig.tight_layout()
plt.show()
```



- The histograms of the variables—production_budget, runtime_minutes, averagerating, and profitability—all show approximately bell-shaped distributions, indicating some similarity to a normal distribution.

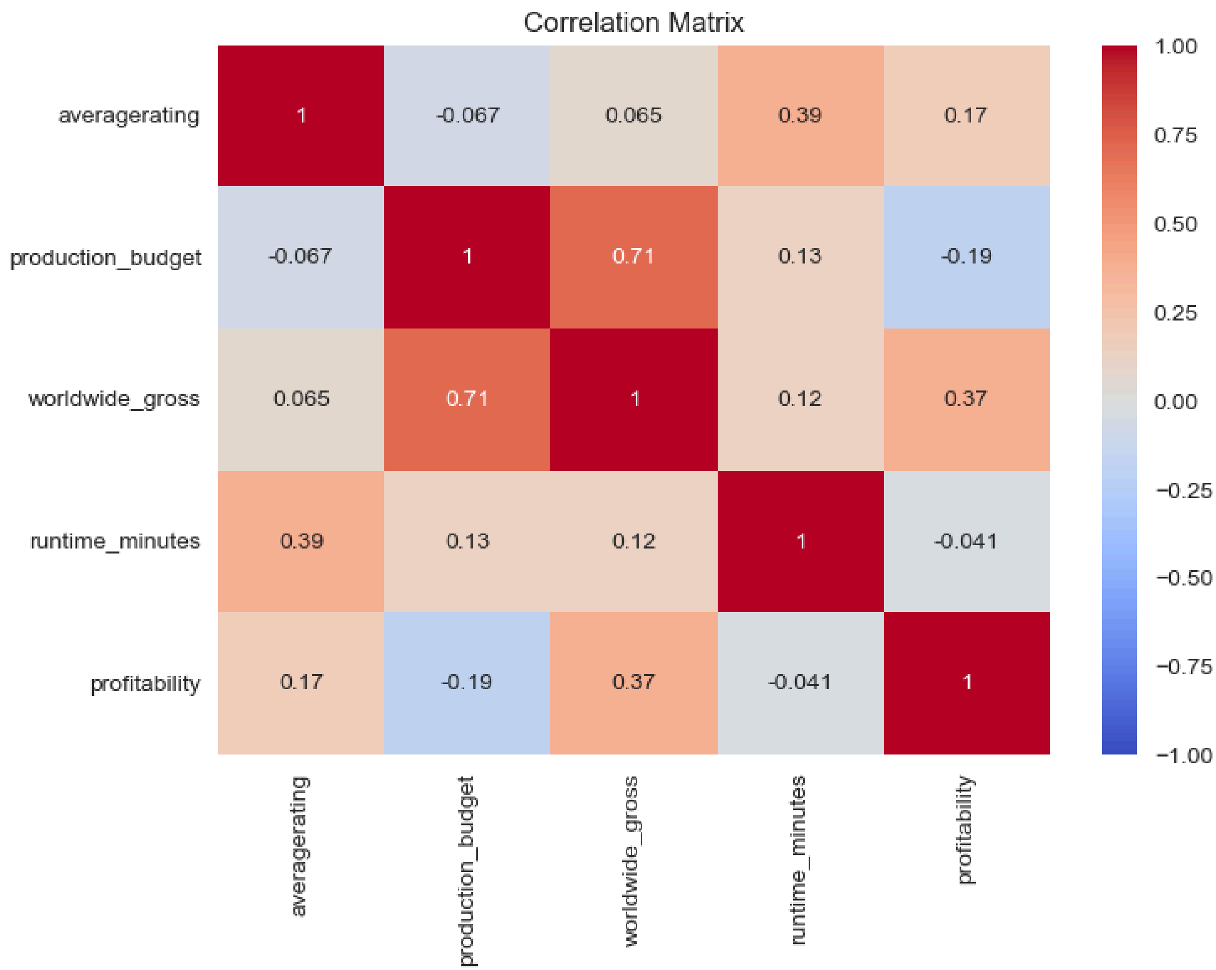
Inferential Analytics

Correlation Analysis

Are there noticeable correlation between the variables in focus?

In [163…

```
# Correlation matrix
corr_matrix = df_cleaned[['averagerating', 'production_budget', 'worldwide_gross','rur
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', vmin=-1, vmax=1)
plt.title('Correlation Matrix')
plt.show()
```



The correlation matrix shows a strong positive relationship between `production budget` and `worldwide gross` (0.71), while profitability is moderately positively correlated with worldwide gross and average rating, and there are weak to no correlations between the remaining variables.

Regression

Is the correlation between the `produaction_budget` and `worldwide_gross` statistically significant?

In [163…

```
# Regress 'production_budget' against 'worldwide_gross'

# Prepare data for regression
X = df_cleaned['production_budget'].values  # Independent variable
y = df_cleaned['worldwide_gross'].values    # Dependent variable

# Perform linear regression using scipy's linregress
slope, intercept, r_value, p_value, std_err = linregress(X, y)

# Calculate R-squared from r_value
r_squared = r_value**2

# Output the results
print(f'R-squared: {r_squared}')
print(f'Coefficient (Slope): {slope}, Intercept: {intercept}')
```

```
R-squared: 0.5002744265512852
Coefficient (Slope): 1.9224699982093725, Intercept: 17362779.133327633
```

- R-squared of 0.50, indicates that `production_budget` explains 50% of the variance in `worldwide_gross`, with a coefficient (slope) of 1.85 and an intercept of 19,705,776

Hypothesis Testing

Test if movie runtimes affect Production budget using a t-test.

In [163…

```
#Hypothesis  Testing: Test if movie runtimes affect Worldwide gross using a t-test.
# Split data by median runtime
median_runtime = df_cleaned['runtime_minutes'].median()
group1 = df_cleaned[df_cleaned['runtime_minutes'] <= median_runtime]['worldwide_gross'
group2 = df_cleaned[df_cleaned['runtime_minutes'] > median_runtime]['worldwide_gross']

# Perform t-test
t_stat, p_val = stats.ttest_ind(group1, group2)
print(f'T-test Statistic: {t_stat}, P-value: {p_val}')
```

```
T-test Statistic: -1.584298960639201, P-value: 0.11347817182130829
```

In [163…

```
#Hypothesis  Testing: Test if Averagerating affect Worldwide gross using a t-test.
# Split data by median runtime
median_runtime = df_cleaned['averagerating'].median()
group1 = df_cleaned[df_cleaned['averagerating'] <= median_runtime]['worldwide_gross']
group2 = df_cleaned[df_cleaned['averagerating'] > median_runtime]['worldwide_gross']

# Perform t-test
t_stat, p_val = stats.ttest_ind(group1, group2)
print(f'T-test Statistic: {t_stat}, P-value: {p_val}')
```

```
T-test Statistic: -1.4725875106164208, P-value: 0.1412130742560257
```

In [163…

```
#Hypothesis  Testing: Test if Production Budget affect Worldwide gross using a t-test.
# Split data by median runtime
median_runtime = df_cleaned['production_budget'].median()
group1 = df_cleaned[df_cleaned['production_budget'] <= median_runtime]['worldwide_gros
group2 = df_cleaned[df_cleaned['production_budget'] > median_runtime]['worldwide_gross

# Perform t-test
t_stat, p_val = stats.ttest_ind(group1, group2)
print(f'T-test Statistic: {t_stat}, P-value: {p_val}')
```

```
T-test Statistic: -21.00079089544458, P-value: 5.9217715870443156e-80
```

In [163…

```
#Hypothesis  Testing: Test if Profitability affect Worldwide gross using a t-test.
# Split data by median runtime
median_runtime = df_cleaned['profitability'].median()
group1 = df_cleaned[df_cleaned['profitability'] <= median_runtime]['worldwide_gross']
group2 = df_cleaned[df_cleaned['profitability'] > median_runtime]['worldwide_gross']

# Perform t-test
t_stat, p_val = stats.ttest_ind(group1, group2)
print(f'T-test Statistic: {t_stat}, P-value: {p_val}')
```

```
T-test Statistic: -14.314396380571242, P-value: 5.1871585026526255e-42
```

- There is a strong correlation between a movie's financial success (worldwide gross) and both its production budget and profitability, while runtime and average rating show no significant impact.

CONCLUSION

- The analysis indicates that movie profitability is influenced by several factors, including genre, release timing, and production budget. Genres such as Music and Horror stand out as particularly profitable, even though they often have lower budgets compared to other genres. Additionally, releasing films during certain months—specifically January, July, and November—tends to maximize box office returns, likely due to favorable seasonal demand. While higher production budgets are correlated with

RECOMENDATIONS

1. Prioritize Genre Selection for Profitability: Focus on Music and Horror genres, which show high profitability potential. These genres often resonate with niche audiences and can achieve strong box office performance without the need for excessive production budgets. This approach allows the studio to tap into reliable revenue streams while managing costs effectively.

2. Implement Seasonal Release Strategy: Schedule film releases during January, July, and November to optimize profitability by aligning with periods of higher consumer interest and lower competition in the box office. Tailoring release schedules to these strategic windows can help new releases capture a larger share of audience attention and boost revenue potential.

3. Allocate Production Budgets Based on Expected ROI: While higher budgets can drive worldwide gross, focus on optimizing budget according to each film’s potential return on investment (ROI), particularly for high-grossing genres. Avoid excessive spending on films where high budgets may not significantly enhance profitability. Instead, prioritize efficient budget use by carefully assessing the target audience, expected revenue, and genre-specific spending norms.

4. Explore Marketing and Audience Engagement Strategies for High-Return Genres: Since profitability varies widely, strengthen marketing strategies tailored to Music and Horror audiences. By effectively engaging fans through targeted advertising and promotional campaigns, the studio can maximize the visibility and appeal of these genres, enhancing box office performance and profitability.

5. Consider Audience Preference Metrics Over Runtime or Rating Increases: Given the weak correlation between runtime and user ratings, focus less on extending runtime for the sake of ratings and more on delivering quality content that aligns with audience preferences. This strategy can prevent unnecessary production costs tied to longer runtimes and instead channel resources into other value-adding areas, such as special effects or casting that enhance the movie's appeal.